APPLYING MULTILEVEL MNL MODEL TO ANALYSE LAND USE INFLUENCE MODE CHOICE BEHAVIOUR IN TAIWAN

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ABSTRACT

This study introduced a multilevel MNL model to explore the unobserved spatial heterogeneity and the impact of land use and public transport provision at district and city/county levels on mode choice between car, motorbike and public transport in Taiwan. The study found that the unobserved spatial heterogeneity does exert significant effects on mode choice behaviour. In addition, by comparing the results from a single-level MNL model and the multilevel MNL model, it was shown that the multilevel MNL model has a better fit but also provides evidence that neglecting the spatial autocorrelation and spatial heterogeneity could create misleading results. This study also found that, in Taiwan, higher population density at the district and city/county levels is associated with a higher probability of choosing public transport over the car and motorbike. However, more diversified land uses and more grid-like street patterns are associated with a higher probability of motorbike use. These results may contribute to planning motorbike management strategies, amongst others, for Southeast Asian countries.

Keywords: land use, multilevel modelling, MNL model, spatial heterogeneity, spatial dependency, mode choice behaviour

1. INTRODUCTION

Creating well-used public transport services requires a good understanding of the relationships between land use, the public transport system and mode choice behaviour [1]. Many policy makers and transport practitioners believe that a well-planned built environment can lead mode choice behaviour towards greater public transport use and reduce dependence on private vehicles.

Many studies have analysed the association between land use and travel behaviour [2, 3]. Specifically, they have found that the density of development, diversity of land uses and design features (layout or form) of the built environment – the 3Ds [4] – impact on travel distances, trip frequencies and mode choice [2, 3]. Although most of the previous studies' results supported the idea that compact and diverse (mixed-use) development could promote transit use, the effects of land-use factors on travel behaviour have been found to be quite varied [2, 3] and have not reached a consistent conclusion due to the varied locations studied, multidimensional aspects of land use and travel behaviour, the different analysis techniques adopted and the scales measured [5].

Several previous studies have stressed that the analysis of the impacts of land use on travel behaviour often involves hierarchically structured data [6, 7]. A hierarchy refers to units grouped at different levels. In the analysis of the effects of land use factors on travel behaviour, individuals' travel behaviour data and zonal area data, such as land-use, often have the features of hierarchical clustering [8]. For example, in a travel mode choice context, individuals are clustered in households and households in districts and districts in cities/counties.

Several studies have suggested that the multilevel modelling method can accommodate these hierarchical features of land use within travel behaviour modelling, and can accommodate zone differences and different geographic scales [6, 7, 9]. Multilevel models can accommodate spatial autocorrelation, spatial heterogeneity, higher-level context, and simultaneous handling of the micro-scale of individuals and the macro-scale of places [8]. Traditional single-level multinomial logit models (MNL) and nested logit (NL) models ignore between group variations and can lead to an inferior data fit [8]. However, only a few studies have adopted a multilevel modelling method to study land use and travel behaviour interrelationships [8-14].

Most previous studies about land use and travel behaviour have focused on North America and Western Europe, which are largely car dominant areas [10, 15-17]. This is of concern as a study by Nijkamp and Pepping (1998)[18], which compared a number of studies from across Europe, concluded that study location significantly affected the results of the demand elasticity. In addition, the mode choice pattern in Taiwan and other countries in Southeast Asia, such as Vietnam, the Philippines, Malaysia and Thailand, are quite different from North America and Western Europe. The motorbike is a popular and important mode of transport in these countries. Yet only a few studies have paid attention to the influence of land use on motorbike use [19]. Chang and Wu (2008)[20] found that motorbike users' behaviour is quite different from car users'. Motorbike use was characterised by shorter trip distances and a greater number of multi-stop trips compared with car use.

This paper uses Taiwan as a case study to analyse the impacts of land use on mode choice behaviour between motorbike, car and public transport. The study builds on a 3-level multilevel multinomial logit (MNL) model to understand the effects of land use features at district-level and city level on individual-level mode choice behaviour accounting for socio-demographic characteristics.

There are six sections in this paper. The next section presents a review of related literatures. The third section describes the study area, data resources and gives some descriptive statistics. The fourth section presents the methodology used in this study. Section 5 discusses the model results. The final section gives conclusions and limitations of this study.

2. LITERATURE REVIEW

Study of the relationship between land-use and mode choice behaviour often involves analysing the relationships between independent variables at a macro-level (aggregate) and micro-level (disaggregate) dependent variables. For example, by assessing the relationship of the population density of an area to an individual's vehicle miles travel (VMT) or mode choice [21]. To understand these macro-micro relations, some studies have aggregated the micro-units to macro-units and analysed the relationships at the macro-unit level [19, 22-24]. Other studies have used disaggregate methods to understand these macro-micro relations using micro-units level [16, 17, 25, 26]. However, both of these methods for dealing with macro-micro relationships are problematic. Aggregated level methods tend to neglect individual variances, leading to issues of ecological fallacy [11]. On the other hand, disaggregation implies that the sample size is arbitrarily increased and may result in a rejection of the null hypothesis more easily [14, 21]. Bhat and Zhao (2002)[27] contended that two issues arise when adopting a disaggregate model for analysing spatial context effects on travel behaviour. First, spatial dependency (also referred as spatial autocorrelation) means that individuals in the same zone may have similar travel behaviour. It occurs because, for example, individuals within the same zone exhibit similar mode choice behaviour due to unobserved factors. Secondly, spatially heterogeneity means that the relationship between mode choice behaviour and explanatory variables could be different across spatial zones. A study of spatial context effects on travel behaviour, which ignores these spatial issues, could lead to inconsistent estimation results. Multilevel models can accommodate these issues [8, 27]. Skrondal and Rabe-Hesketh (2004) [28] asserted that the advantage of multilevel modelling is that it allows multiple levels of data, ranging from micro-units to macro-units, to be dealt with simultaneously.

Multilevel modelling techniques have been used in several travel studies. Most of these studies used a model form with a linear structure and continuous dependent variables, such as travel distance, travel time, vehicle miles travel (VMT) and trip frequency [11-14, 29]. Schwanen et al. [13] employed a four-level (individual, household, residential and regional) multilevel regression model to analyse the influence of urban form on mode choice, travel time and travel distance for commuters in the Netherlands. Snellen et al. [14] studied the relationships between individual level socio-demographic characteristics, neighbourhood level land-use variables, and mode choice for frequently conducted activities. They found that urban land use variables only had a modest influence on the dependent variable. Antipova et al. [11] used a two-level (individual and neighbourhood) multilevel modelling method to analyse the impact of land use on commuting distance and time. Li et al. [12] also used a two-level (neighbourhood and residential) multilevel model. They analysed the relationship between built environment and walking activity for senior people. Nevertheless, only limited attention has previously been given to applying multilevel models to discrete responses. This study adopts a 3-level multilevel discrete choice model to analyse the land use features and spatial heterogeneity at the district and city/county levels on individual mode choice between motorbike, car and public transport in Taiwan accounting for social-demographic characteristics.

3. CASE STUDY AND DATA

Taiwan is categorized as an Asian high-income country with compact cities and a high propensity for car ownership [30]. Taiwan has an area and population of about 36000 km^2 and 23 million respectively, and a population density of over 640 persons/km^2[31]. Although Taiwan has a range of public transport systems, including bus, metro, rail and high speed rail, the car and motorbike are still the dominant modes of transport, with a modal split of total daily motorised trips of 24.8% and 46.5%, respectively. Public transport accounts for 16.0% of total daily motorised trips [32].

In this study, a 3-level multilevel analysis approach is adopted. The 3-level includes individual-level, districts-level and city/county-level. The individual-level refers to the attributes relates to each respondent. The district-level and city/county-level refer to the different geographic scale. The impacts of land use factors on individuals' mode choice behaviour are examined at the district-level and city/county-level. There are 348 districts clustered in 19 cities/counties in Taiwan. The average area and population of the districts and cities/counties are 102 km^2 and 66,000 residents for each district and about 1,800 km^2 and 1,210,000 residents for each city/county respectively.

The travel behaviour data used in this study is drawn from Taiwan's 2011 Mode Choice Behaviour Survey [33]. This postal survey was conducted by the Taiwanese Institute of Transportation during September and October 2011. Data for the survey was collected from randomly selected households from a list of addresses with a registered car or motorbike, provided by Taiwanese Directorate General of Highways. This list was used because it was not possible to access a complete address list for Taiwan. Because levels of motorbike and car ownership are high in Taiwan, only 5% of households were excluded on this basis. Those households excluded from sampling are categorised as household without car and motorbike, which are tend to use public transport more. Therefore, the samples' share of car and motorbike could be somewhat higher than the population's share of car and motorbike. Every household on the list had equal chance to be selected no matter their level of car or motorbike ownership. Fifty thousand selected addresses were sent two questionnaires, one of which was to be completed by any vehicle owners and the other by any non-vehicle owners within the household over the age of 10. A total of 6,860 questionnaires were completed (3,828 vehicle owners and 3,032 non-vehicle owners); overall response rate is 6.8% (7.7% for vehicle owners, 6.1% for non-vehicle owners). After chi-square test, there is no significant difference in the distribution of age, gender between sample and population. Also, the samples covered all the household type and occupancy.

Respondents were asked to report the features of their most frequent trip during a week. Trip features asked about included mode choice (among bus, metro, train, car and motorbike), trip purpose, trip frequency, trip origin and destination, travel cost, travel time, and service satisfaction. Travel cost refers to the out-of-pocket monetary cost of the trip. For car and motorbike users, this includes parking costs and fuel costs but nothing towards the cost of vehicle purchase, tax, insurance and maintenance. For public transport users, this cost equals the fare paid if respondents hold seasonal tickets such as monthly tickets, are asked to convert to single trip cost according to their monthly trips.

A number of socio-demographic characteristics (gender, age, education, job and wage, and whether they had a car and/or motorbike driver's licence) were also collected for each respondent. At the household level, data was collected on the number of cars, motorbikes and bicycles within the household, household size, the total number of driver's licences held, and household income.

After removing incomplete responses, this gave a valid sample size of 5,356 individuals. Among all the trips, the trip origins covered 289 districts of all 348 districts and covered all 19 cities/counties in Taiwan. Within the sample, 20.5% of trips were made by public transport, 47.0% by motorbike, and 32.5% were by car. The differences between the modal split of this study's sample and the national survey may be because the postal survey adopted by Taiwan's 2011 Mode Choice Behaviour Survey neglected about 5% of the households without any motorbike and car registered. In addition, the questionnaire of Taiwan's 2011 Mode Choice Behaviour Survey only asked the respondents about their most frequent trip and did not ask them to record their travel diary.

It should be noted that the trip data used in this study only covers frequent trips reported by respondents and does not include all trips made by them. This means that commuting trips and school trips are likely to be over represented in the data set, and social and leisure trips are likely to be underrepresented. Some of the tour features, such as stops or transfers within the trips are not reported in the survey.

Table 1 show the relationships between sociodemographic characteristics and mode choices. In Taiwan, a greater proportion of males use the car, whilst a higher proportion of females use public transport. Use of the motorbike is evenly split between males and females. The samples' gender ratio of female to male is 50.6% to 49.4%. The chi-square test shows that we cannot reject the hypothesis that the samples' gender ratio is the same as Taiwan's population gender ratio of 49.9% to 50.1% [34]. Table 1 also shows that the groups of people aged under 14 and 15-24 have higher proportion to use public transport over car and motorbike. This maybe because people cannot have a car and motorbike driver's license until the age of 18 in Taiwan due to the regulation. Car and motorbike users under age 18 are passengers driving by their parents or someone else. Age groups between 15 and 34 have the highest percentage of motorbike use, and age groups between 35 and 54 have the highest percentage of car use. The may reflect to people's mode shift from motorbike to car along with their age increase and social status changes. In addition, for occupancy, students have the highest percentage of choosing public transport compared to other occupancy.

The driver's license ownership and children in household associate with mode choice, as shown in Table 1. The percentage of respondents who own car driver's license and use car is more than twice as the percentage of respondents who do not own car driver's license and use car as passengers. Likewise, the percentage of respondents who own motorbike driver's license and use motorbike is about twice as the percentage of respondents who do not own motorbike driver's license and use motorbike as passengers. Respondents with children (under 18) in households have much higher percentage of using car than respondents without children in household because the responsibility of transport their children.

Table 1 Gender, age and mode choice

Gender	Mode choice	Frequency	Percent
Female	Car	841	30.7
	Motorbike	1294	47.2
	Public transport	606	22.1
	Total	2741	100.0

Male	Car	901	34.5
	Motorbike	1220	46.7
	Public transport	493	18.9
	Total	2614	100.0
Age			
Under 14	Car	33	27.0
	Motorbike	49	40.2
	Public transport	40	32.8
	Total	122	100.0
15-24	Car	90	13.8
	Motorbike	329	50.4
	Public transport	234	35.8
	Total	653	100.0
25-34	Car	341	26.3
	Motorbike	712	54.9
	Public transport	244	18.8
	Total	1297	100.0
35-44	Car	520	40.8
	Motorbike	554	43.4
	Public transport	202	15.8
	Total	1276	100.0
45-54	Car	445	39.0
	Motorbike	493	43.2
	Public transport	203	17.8
	Total	1141	100.0
55-64	Car	245	38.4
	Motorbike	268	42.0
	Public transport	125	19.6
	Total	638	100.0
65 and over	Car	68	29.8
	Motorbike	109	47.8
	Public transport	51	22.4
	Total	228	100.0
Occupancy			
Student	Car	121	16.8
	Motorbike	327	45.3
	Public transport	274	38.0
	Total	722	100.0
Public servant	Car	281	43.8
	Motorbike	254	39.6
	Public transport	107	16.7
	Total	642	100.0
Technology industry	Car	199	37.5
	Motorbike	251	47.4
	Public transport	80	15.1
	Total	530	100.0
Financial industry	Car	68	34.5
	Motorbike	74	37.6
	Public transport	55	27.9
	Total	197	100.0
Business and service industry	Car	346	35.6
	Motorbike	463	47.6
	Public transport	163	16.8
	Total	972	100.0
Other service industry	Car	365	32.9
	Motorbike	564	50.8
	Public transport	181	16.3
	Total	1110	100.0
Housekeeper	Car	181	28.5
	Motorbike	325	51.3
	Public transport	128	20.2

		Total	634	100.0
Others		Car	181	33.0
		Motorbike	256	46.7
		Public transport	111	20.3
		Total	548	100.0
Car driver's license owned or not	Yes=1	Car	1563	37.1%
		Motorbike	1971	46.8%
		Public transport	678	16.1%
		Total	4212	100.0%
	No=0	Car	179	15.6%
		Motorbike	544	47.6%
		Public transport	421	36.8%
		Total	1144	100.0%
Motorbike driver's license owned or not	Yes=1	Car	1502	32.5%
		Motorbike	2333	50.4%
		Public transport	790	17.1%
		Total	4625	100.0%
	No=0	Car	240	32.8%
		Motorbike	182	24.9%
		Public transport	309	42.3%
		Total	731	100.0%
Children (age under 18) in household or not	Yes=1	Car	915	36.0%
		Motorbike	1130	44.4%
		Public transport	499	19.6%
		Total	2544	100.0%
	No=0	Car	827	29.4%
		Motorbike	1385	49.3%
		Public transport	600	21.3%
		Total	2812	100.0%

Table 2 shows the descriptive of income, household car ownership, household motorbike ownership, travel cost and OD distance compared with different mode choice groups. For personal income and household income per month, car users have the highest average income level (US$1,400 and US$2,900 for personal income and household income respectively) than motorbike (US$1,000 and US$2,400 for personal income and household income respectively) and public transport users (US$1,000 and US$2,700 for personal and household income respectively). For household car ownership and household motorbike ownership, car users have the highest average household car ownership (average 1.6 cars per household) than motorbike and public transport users. Also, motorbike users have the highest average household motorbike ownership (average 2.4 motorbikes per household) than other mode groups.

In terms of travel cost, car users have the highest average travel cost, US$2.3 compared with motorbike and public transport users. Travel cost refers to out of pocket cost, which includes fuel cost and parking cost for car and motorbike, and fare cost for public transport. The respondents who hold season tickets such as monthly tickets were asked to convert to single trip costs according to their monthly trips.

OD distance is included in this study is to examine the impacts of spatial distance between trip origins and destinations on mode choice behaviour. As precise origins and destinations were not known, it was calculated using the Euclidean distance between the trip origin district and trip destination district centroids. The district centroids were found by calculating the median centres, which minimize the overall Euclidean distance to the points of interests (POI) in each district. The POI data was supplied by Taiwanese Institute of Transportation, and included government offices, education facilities and public services. Trips that originated and ended within the same district were assigned an OD distance of 3 km. This distance (3km) is approximately half the average radius of the districts. Table 2 shows that car users have the longest average OD distance (8.8 km) ranging from about 1.2km to 166.8km and motorbike users have the shortest OD distance (6.3km) ranging from about 1.2km to 53.9km.

The distribution of OD distance for each mode reflects the service ranges for those modes. Table 2 shows that car enjoys the widest service range between the minimum of 1.2 km and maximum of 166.8 km than motorbike and public transport. Although there is some short trip use for cars, the average OD distance for car is the longest compared to motorbike and public transport. It seems that the car serves mainly for middle to long range trips. On the other hand, motorbike has the shortest average OD distance and smallest OD distance standard deviation, which means that motorbike may mainly serve for the shortest range trips due to the features of easy to use and free charging of parking in most cities in Taiwan. With trip distance increasing, travellers tend to use public transport and car instead of motorbike, possibly due to the increasing risks and discomfort for motorbike. In terms of public transport, the minimum OD distance is longer than that for motorbike and car, which may mean that for some short distance trips public transport users tend to walk or cycle rather than use public transport. The average OD distance for public transport is in between car and motorbike, which means that public transport may mainly cover the middle range trips in Taiwan. As trip distance increases, travellers would tend to use the car rather than public transport, possibly due the increasing in-vehicle time, transfers and waiting time. Although travel time was not included in this study, the OD distance this study adopted can reflect the some of the features of car, motorbike and public transport.

Table 2 Income, motorised vehicle ownership and mode choice

Items		Min.	Max.	Mean	Std. Deviation
Car	Personal income per month (US$ 1,000[1])	.3	3.3	1.4	.85
	Household income per month(US$ 1,000[1])	.7	7.50	2.9	1.79
	Household car ownership	0.0	6.0	1.6	.82
	Household motorbike ownership	0.0	8.0	1.7	1.19
	Travel cost (US$[1])	0	14	2.3	2.05
	OD distance	1.2	166.8	8.8	8.81
Motorbike	Personal income per month (US$ 1,000[1])	.3	3.3	1.0	.67
	Household income per month(US$ 1,000[1])	.7	7.5	2.4	1.58
	Household car ownership	0.0	6.0	1.2	.79
	Household motorbike ownership	0.0	8.0	2.4	1.20
	Travel cost (US$[1])	0	12.7	1.0	1.20
	OD distance	1.2	53.9	6.3	5.59
Public transport	Personal income per month (US$ 1,000[1])	.3	3.3	1.0	.76
	Household income per month(US$ 1,000[1])	.7	7.5	2.7	1.71
	Household car ownership	0.0	5.0	1.2	.75
	Household motorbike ownership	0.0	6.0	1.9	1.18
	Travel cost (US$[1])	0	6.7	1.0	0.98
	OD distance	1.7	50.9	7.7	6.77

The data from the Mode Choice Behaviour Survey is supplemented with land use data. The land use data is drawn from the Taiwanese National Land Surveying and Mapping Centre, at a resolution of 1/25,000. A number of land use variables are estimated at the district level: population density, job density, land use mix entropy, and the proportion of 4-way intersections (% of 4-way intersection). Figure 1 shows the land use measurements at district-level and city/county-level in Taiwan.

Table 3 gives the mean, standard deviation for the land use variables at district-level and city/county level included in the model. For land use mix entropy, which indicates the extent of land use diversity, was calculated as Eq. (1) based on six land use categories: residential,

[1] Exchange rate: US$:NT$(New Taiwan Dollar)=1:30

commercial, industrial, government offices, educations, and hospital and social care buildings. Land use entropy ranges from 0 to 1 in which higher entropy value indicates that a more evenly distributed mix of land uses.

$$Land\ use\ mix\ entropy = -\sum_j P_j \times \frac{\ln(P_j)}{\ln(J)} \tag{1}$$

Where P_j is the proportion of land use type j in the area, and J is the total number of land use types, which equals to 6.

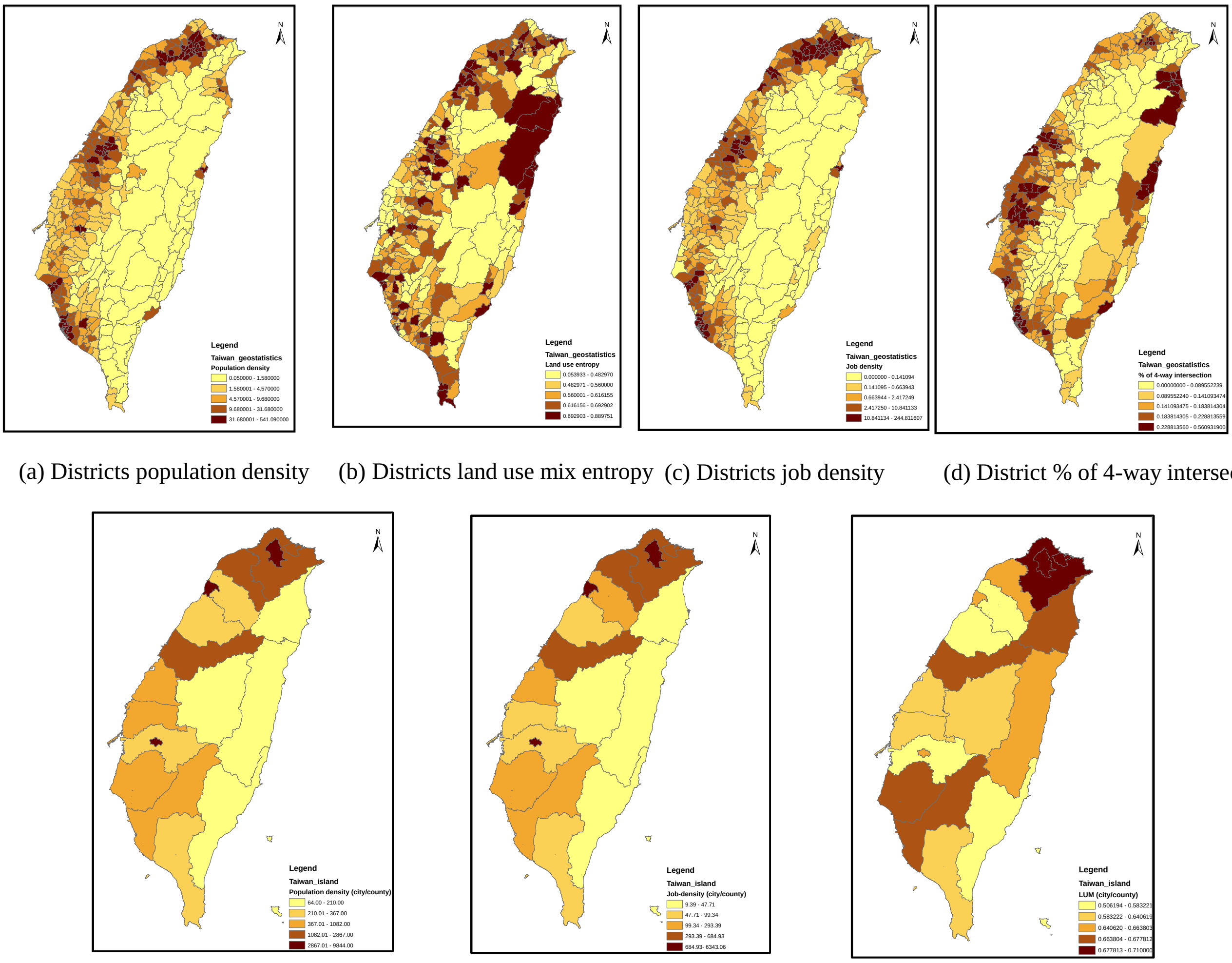
The proportion of four-way intersections indicates the extent of grid-like street pattern [4]. These were extracted from the mapping data of Taiwanese Traffic Network Digital Map using ArcGIS 10.2 package. The road network included all the road types, such as provincial road, city/county road, and load road, except highways.

According to the authors' previous study [35], population density is significantly associated with mode choice between car, motorbike and public transport at trip origins, and job density is significantly associated with mode choice at trip destinations in Taiwan. So, Population density is adopted as explanatory variable at district-level. At the city/county-level factor analysis was adopted to combine city/county's population density and job density into density variable. Most trips (81%) have their trip origins and destinations within the same city or county, and there is a high correlation between population density and job density (0.99) at this level. Thus it made sense to have a combined density measure at the city/county level.

The trip-related and socio-demographic variables adopted in this study were determined using a stepwise test to check if there were significant relations between the chosen variables and mode choice behaviour. The resulting variables selected to be included in the models were: trip purpose of work and school, and individual socio-demographic characteristics – age, gender, personal income, car driver's license and motorbike driver's license, children in household, and household car and motorbike ownerships as controlling factors. From the literature, these have been shown to be important determinants of mode choice.

TABLE 3 Land use statistics for Taiwanese districts and city/county

Variables	Definition at district level	Districts		Cities/counties	
		Mean	SD	Mean	SD
Population density	Population/area size(persons/ha)	83.77	96.62	22.59	28.39
Job density	Employment/area size(jobs /ha)	34.12	50.23	11.10	19.14
Land use mix entropy	Mixture of residential, commercial, industrial, government offices, educations, and hospital, social care buildings	0.65	0.11	0.66	0.04
% of 4-way intersection	Proportion of four-way intersections	0.22	0.07	--	--
Density (city/county-level)	Factor analysis combines population density and job density at city/county level	--	--	0.00	1.00



(a) Districts population density (b) Districts land use mix entropy (c) Districts job density (d) District % of 4-way intersection

(e) City/county population density (f) City/county job density (g) City/county land use mix entropy

FIGURE 1 Districts features in Taiwan

4. Methodology

The purpose of the model in this study to examine the impacts of land use variables at the different geographical scales of district and city/county on mode choice behaviour between car, motorbike and public transport, whilst capturing the spatial heterogeneity at these geographical scales. The multilevel MNL model is based on a MNL model with a linear predict function. It allows the intercept of the utility functions to vary randomly over clusters. The predict function of the multilevel MNL model includes two parts, a fixed part and a random part. In order to capture the spatial heterogeneity, two random terms (combined as the random part) are included in the utility functions. The fixed part of the model includes individual level variables (trip-related, socio-demographic, and travel-related level of service variables), and land use and public transport provision variables at district-level and city/county-level.

Assuming a three-level multilevel MNL model, the predict function can be expressed as

$$y_{ijk}^{m} = \beta_{0jk} + \beta_{ijk} x_{ijk} + \epsilon_{ijk}, \tag{2}$$

Where i denotes the individual-level, district-level is denoted by j, city/county-level is denoted by k, and m denotes predict function for different alternatives: car, motorbike and public transport. y_{ijk} is the individual i's response between car, motorbike and public transport, and

x_{ijk} is the individual-level's explanatory variables such as gender, age, monthly income, car driver's license, motorbike driver's license, children in household, trip purpose and trip distance in this study, and the subscript *j* and *k* means that individuals are clustered in districts-level and in city/county-level. β_{0jk} is district-level specific intercepts which reflects the variance between districts. β represents coefficients for x_{ijk}. The items in Eq. (2) with subscriptions of *i, j* and *k* mean that the items are at the individual-level. ϵ_{ijk} is the individual-level residual terms.

If β_{0jk} is allowed to vary across districts and adds district-level contextual variables such as population density, job density, land use mix and the proportion of four-way intersection to explain the variance of β_{0jk} (between districts variance), then the district-level model can be expressed as follows:

$$\beta_{0jk} = \gamma_{0k} + \mu_{jk}\omega_{jk} + \zeta_{jk} \text{ (district-level model),} \tag{3}$$

Where γ_{0k} denotes city/county-level specific intercepts, ω_{jk} denotes district-level explanatory variables, and μ_{jk} denotes coefficients for the district-level explanatory variables. ζ_{jk} denotes the district-level residual terms representing spatial heterogeneity between districts. The items in Eq. (3) with subscriptions of *j* and *k* mean that the items are at the district-level.

If γ_{0k} is allowed to vary across city/county and adds city/county-level contextual variables such as density and land use mix to explain the variance of γ_{0k} (between city/county variance), then city/county-level model can be expressed as following:

$$\gamma_{0k} = \pi_0 + \rho_k\theta_k + \psi_k \text{ (city/county-level model),} \tag{4}$$

Where π_0 denotes city/county-level specific intercepts, θ_k denotes city/county-level explanatory variables, and ρ_k denotes coefficients for the city/county-level explanatory variables. ψ_k is the city/county-level residual terms representing spatial heterogeneity between city/county. The items in Eq. (4) with subscriptions of k mean that the items are at the city/county-level.

Substituting the city/county level model and district-level model for the coefficients γ_{0k} and β_{0jk} in equation (4) and equation (3) into the individual-level model in equation (2), we obtain the reduced form as follows:

$$y_{ijk}^{m} = \pi_0 + \beta_{ijk}x_{ijk} + \mu_{jk}\omega_{jk} + \rho_k\theta_k + \zeta_{jk} + \psi_k + \epsilon_{ijk} \quad \text{(reduced form)} \tag{5}$$

Where π_0 is constant of the function, ($\beta\ \ x_{ijk} + \mu_{jk}\omega_{jk} + \mu_{jk}\omega_{jk}$) is fixed part of the function and ($\zeta_{jk} + \psi_k + \epsilon_{ijk}$) is random part of the function. Random terms at the district-level and city/county-level are assumed to be normally and identically distributed, and random terms at different levels are independent.

$$\zeta_{jk} \sim N\left(0, \sigma_{\zeta_{jk}}^2\right), \psi_k \sim N\left(0, \sigma_{\psi_k}^2\right)$$

The random terms at the individual-level, ϵ_{ijk}, are independent and identically distributed with Gumbel (type 1 extreme value) distribution with a variance (σ_{ϵ}^2) of $\pi^2/6$ [36].

Then a multinomial logit link function can be denoted as

$$\Pr(Y_{ijk} = m) = \frac{\exp(y^m)}{1+\sum_{s=2}^{M}\exp(y^s)} \tag{6}$$

The discrete dependent variable of this study is mode choice between car, motorbike and public transport. Increasing public transport use is an important policy goal within Taiwan's National Road Public Transport Plan [37]. Gaining a better understanding of the extent to which land use characteristics and public transport provision influence mode choice between car and public transport, and between motorbike and public transport can help decision-makers plan better land use and transport integration strategies to fulfil this policy goal. Therefore, public transport was set as the of interest (reference) category.

The intra-class correlation coefficient (ICC) refers to the proportion of between group variance to total variance [21]. It is also equal to the correlation between values of two randomly drawn individuals in the same, randomly drawn group [21]. ICC is calculated by divided the between-group variance by the total variance. The between-group variance in this study means the mode choice behaviour difference between districts or city/county. Therefore, the index can represent the spatial heterogeneity of mode choice behaviour across districts and cities/counties, and can capture spatial autocorrelations among individuals within the same districts and cities/counties and recognise spatial heteroscedasticity [10]. The ICC values for empty models (a model only adopts random effects without any explanatory variable) of linear regression models often range between 0.10 and 0.25 [21]. A greater ICC value for empty model indicates that adoption of the multilevel model is meaningful. Using the notation of this study, the ICC for mode choice of car (*m=car*), for example, can be expressed as

$$ICC^m = \frac{\sigma^2_{\zeta^m_{jk}} + \sigma^2_{\psi^m_k}}{\sigma^2_{\zeta^m_{jk}} + \sigma^2_{\psi^m_k} + \sigma^2_{\epsilon^m_{ijk}}} \tag{7}$$

5. RESULTS

This section presents the results of the model estimation. Three models were estimated. Model A is a multilevel MNL model with only adopting individual-level variables. The purpose of Model A is to test the ICC values to see whether there is significant spatial heterogeneity or not. Model B is a single-level MNL model, which includes district-level and city/county-level explanatory variables within the same level. Model C is a 3-level multilevel MNL model which allowed intercepts to be varied randomly across district-level and city/county-level. This model includes travel-related attributes at the individual level, land use and public transport provision variables at district-level and city/county-level, and accounted for socio-demographic characteristics. The models' estimation was conducted using MCMC (Markov Chain Monte Carlo) procedures within the MLwiN package. These models were first run using restricted iterative generalized least square (RIGLS) to establish a prior distribution, follow by MCMC estimation using Gibbs sampling, with 2,000 burn in iterations and 300,000 iterations to get the posterior distribution. Table 4 summarises the estimation results of the three models.

The reason for estimating Model A is to determine whether the adoption of a multilevel MNL model was justified. It depends on the significance of the spatial heterogeneity parameters representing the unobserved variations in utility functions and the level of ICC (intra-class correlation coefficients) values. Table 4 shows that all the spatial heterogeneity parameters for car and motorbike at district-level and city/county-level in Model A are significant. In addition, the ICC^{Car} and $ICC^{Motorbike}$ (intra-class correlation coefficient) across district-level and city/county-level, are 0.102 and 0.134, respectively, indicating that correlations for individuals at the same district and city/county are 10.2% and 13.4%, respectively. The high level of spatial heterogeneity at district-level and city/county-level implies that the spatial heterogeneity cannot be ignored and there is a need to adopt multilevel modelling technique to accommodate spatial issues of this study.

With respect to the models' complexity and fit, the DIC (Deviance Information Criterion) (see Table 4) values suggest that Model C (Multilevel MNL model) is the best model among the three models. The DIC, which is the sum of the number of effective parameters (pD) and the deviance of MCMC, represents the model's complexity and fit, and may be used for comparing models[38]. The number of effective parameters refers to the complexity of a model and the deviance statistic refers to a model's fit. Since increasing complexity is trade-off by a better model's fit. Spiegelhalter, Best [38] suggested that adds the model's fit (deviance of MCMC) and complexity (the number of effective parameters) to form the DIC (Deviance Information Criterion) for comparing models with the same structure or different structure. After adding spatial heterogeneity into the model, the DIC for model C reduced by around 40 compared with Model B. Although the number of effective parameters for Model C is 53 points higher than Model B, the deviance of MCMC for Model C, 9690.47, is about 99 points lower than Model B. Therefore, in the remainder of this section, the estimation results of Model C will be discussed and interpreted.

The last column in Table 4 refers to the subtraction the absolute t-value for district-level and city/county-level variables in Model C from the absolute t-value for district-level and city/county-level in Model B. Most of the absolute t-values' difference between Model B and Model C are positive, except land use entropy at district-level for car and motorbike, and city/county-level for motorbike. In addition, comparing the coefficients' significant-level for density and % of 4-way intersection at district-level, these coefficients are significant at the 95% level in Model B but insignificant in Model C. This comparison provides evidence that, under the circumstances of high spatial autocorrelation, ignoring the spatial between-group difference by using a single-level discrete choice model (Model B) may exaggerate the coefficients' significance and lead to spurious results [14, 21].

With respect to controlling factors of individual's socio-demographic factors and trip purpose in Model C, as shown in Table 4, Males tend to use motorbike more than public transport compared with females. Students are more likely to use public transport rather than car and motorbike compared to other occupation groups. Personal income shows opposite results between the mode choice of car and public transport, and motorbike and public transport. With increasing personal income, people are more likely to choose car over the public transport but would choose public transport over the motorbike. As for trip purpose, work and school trips are more likely to be made by public transport than by car while work trips are more likely to be made by motorbike than by public transport. Car and motorbike driver's licenses also have significantly positive effects on car and motorbike use respectively.

With respect to household socio-demographic factors, households with children age under 18 in the household tend to have a higher probability of car use than public transport use. Likewise, households with higher car or motorbike ownership are more likely to use the car or motorbike respectively.

As for travel related attributes in Model C, as shown in Table 4, OD distance and travel cost have the opposite signs for people choosing between car and motorbike over public transport. With increasing OD distance, people tend to choose public transport rather than motorbike. On the other hand, higher travel costs intend to encourage car and motorbike use rather than public transport use.

After accounting for the controlling factors, the Model C results, as shown in Table 4, indicate that land use variables exert significant influence on mode choice behaviour. At the district-level, increasing population density and job density is significantly associated with a greater probability of choosing public transport over the car and the motorbike. On the other hand, the proportion of 4-way intersection – representing grid-like street pattern – shows strong association with motorbike and car use, which means that people in the districts with more gird-like street pattern tend to choose motorbike rather than public transport. Districts with more evenly distributed land uses – higher land use entropy values – tend to have more car use than public transport but tend to have more car and motorbike use than public transport (though not significant at the 95% level). In terms of the city/county-level, increasing density is associated with a higher probability of choosing public transport over the car and the motorbike, although the significant level for car is only at 90%.

The covariance of the random part refers to the correlation between car and motorbike use at district-level and city/county-level. The positive covariance at district-level and city/county-level means that districts and city/ county in Taiwan have higher proportion of car use also have high proportion of motorbike use.

With respect to spatial heterogeneity (random terms), Model A, as shown in Table 4, shows that spatial heterogeneity parameters at district-level and city/county-level are at the level of significance of 90% and 95% respectively. It means that there is significant spatial heterogeneity (unobserved factors) influence mode choice behaviour between districts and cities/counties.

Table 4 Results

		Model A Null Multilevel MNL model			Model B Single-level MNL model			Model C Multilevel MNL model			Absolute t-value in model B minus absolute t-value in Model C
	Fixed Part	B	S.E.	t-value	B	S.E.	t-value	B	S.E.	t-value	
Car	**Individual-level**										
	Intercept	0.63	0.10		-1.86	0.91	-2.05	-2.20	1.47	-1.50	
	Gender (Male=1)				0.14	0.09	1.54	0.15	0.09	1.69	
	Age under 14				0.58	0.33	1.78	0.59	0.33	1.75	
	Age between 15-24				**-0.55**	**0.23**	**-2.43**	**-0.57**	**0.23**	**-2.50**	
	Occupancy (Student=1)				**-0.60**	**0.23**	**-2.58**	**-0.61**	**0.24**	**-2.58**	
	Monthly personal income (US$1,000)				**0.30**	**0.06**	**4.70**	**0.30**	**0.06**	**4.81**	
	Car driver's license				**0.82**	**0.11**	**7.33**	**0.82**	**0.12**	**7.17**	
	Children (under 18) in Household				**0.36**	**0.09**	**4.07**	**0.36**	**0.09**	**4.01**	
	Household car ownership				**0.54**	**0.05**	**12.09**	**0.54**	**0.05**	**11.89**	
	Trip purpose (work=1)				-0.14	0.10	-1.35	-0.15	0.10	-1.46	
	Trip purpose (School=1)				0.05	0.19	0.27	0.04	0.20	0.21	
	Travel cost				**0.59**	**0.04**	**15.03**	**0.60**	**0.04**	**14.90**	
	OD distance				-0.01	0.01	-0.83	-0.01	0.01	-0.83	
	District-level										
	Density				**-0.16**	**0.04**	**-4.30**	**-0.10**	**0.05**	**-2.02**	2.28
	Land use mix				0.01	0.39	0.01	0.02	0.46	0.04	-0.03
	% of four-way intersection				**3.41**	**0.74**	**4.61**	**1.71**	**0.98**	**1.75**	2.85
	City/county-level										
	Density				**-0.23**	**0.04**	**-5.30**	**-0.24**	**0.13**	**-1.93**	3.37
	Land use mix				-1.27	1.32	-0.96	-0.27	2.23	-0.12	0.84
Motorbike	**Individual-level**										
	Intercept	0.92	0.11		-2.45	0.82	-3.01	-2.84	1.35	-2.10	
	Gender (Male=1)				**0.17**	**0.08**	**2.13**	**0.18**	**0.08**	**2.23**	
	Age under 14				0.16	0.28	0.56	0.16	0.28	0.55	
	Age between 15-24				0.03	0.18	0.18	0.03	0.18	0.15	
	Occupancy (Student=1)				**-0.60**	**0.19**	**-3.14**	**-0.61**	**0.19**	**-3.15**	
	Monthly personal income (US$1,000)				**-0.19**	**0.06**	**-3.11**	**-0.18**	**0.06**	**-2.97**	
	Motorbike driver's license				**1.32**	**0.11**	**12.03**	**1.32**	**0.11**	**11.93**	
	Children (under 18) in Household				0.15	0.08	1.85	0.14	0.08	1.75	
	Household car ownership				**0.35**	**0.03**	**12.93**	**0.35**	**0.03**	**12.32**	
	Trip purpose (work=1)				0.16	0.09	1.75	0.16	0.09	1.73	
	Trip purpose (School=1)				0.18	0.16	1.07	0.16	0.17	0.96	
	Travel cost				0.05	0.04	1.33	0.05	0.04	1.29	
	OD distance				**-0.04**	**0.01**	**-6.67**	**-0.04**	**0.01**	**-6.67**	
	District-level										
	Density				**-0.13**	**0.03**	**-4.16**	**-0.09**	**0.04**	**-2.31**	1.85
	Land use entropy				0.62	0.35	1.76	0.75	0.41	1.85	-0.09
	% of four-way intersection				**3.78**	**0.67**	**5.63**	**2.29**	**0.86**	**2.66**	2.97
	City/county-level										
	Density				**-0.23**	**0.04**	**-5.90**	**-0.24**	**0.11**	**-2.12**	3.77
	Land use entropy				0.99	1.17	0.85	1.92	2.04	0.94	-0.09
Random part	**City/county-level**										
	$\sigma^2_{\psi^{car}_{00k}}$	0.151	0.067	2.254				0.110	0.062	1.774	
	$Cov(\sigma^2_{\psi^{car}_{00k}}, \sigma^2_{\psi^{motorbike}_{00k}})$	0.151	0.072	2.097				0.068	0.047	1.447	

$\sigma^2_{\psi_{00k}^{car}}$	0.214	0.092	2.326				0.092	0.051	1.804
District-level									
$\sigma^2_{\zeta_{0j}^{car}}$	0.036	0.022	1.636				0.073	0.038	1.921
$Cov(\sigma^2_{\zeta_{0j}^{car}}, \sigma^2_{\zeta_{0j}^{motorbike}})$	0.002	0.016	0.125				0.030	0.023	1.304
$\sigma^2_{\zeta_{0j}^{motorbike}}$	0.040	0.021	1.905				0.029	0.019	1.526
DIC (Deviance Information Criterion)		10988.85			9246.26			9206.34	
MCMC deviance		10903.69			9210.41			9111.78	
pD (the effective number of parameters)		83.69			34.85			88.00	

6. DISCUSSION AND CONCLUSION

This study introduced a multilevel MNL model to explore unobserved spatial heterogeneity and the impact of land use variables at district and city/county level on mode choice between car, motorbike and public transport.

The results of this add to the growing body of evidence that land use variables: density, mixed land use and street design, apply influence on travel behaviour after accounting for socio-demographic and travel-related attributes.

This study found that the unobserved spatial heterogeneity (spatial between-group variations) do exert significant influence on mode choice behaviour. The model's fit of Model C improved by adopting unobserved spatial heterogeneity compared to Model B. In addition, by comparing the results of traditional single-level MNL model and multilevel MNL model, it provides further evidence that previous studies by adopting single-level MNL model, which neglected spatial dependency and spatial heterogeneity, to analyse the relationships between land and travel behaviour could exaggerate the sample size and cause misleading results [14, 21]. Therefore, for the studies related to hierarchical clustered features and hierarchical data structure, multilevel modelling techniques may be a better method leading to a more accurate results.

After accounting for district-level and city/county-level land use, the unobserved spatial heterogeneity at city/county-level was reduced greatly compared to the random term in Model A; this means that the unobserved spatial heterogeneity was effectively explained at city/county-level by the land use and public transport provision variables adopted in this study.

Overall, this study found that socio-demographic characteristics and travel-related attributes exert significant influence on mode choice behaviour. At the individual-level, age, personal income, car and motorbike driver's license ownerships, travel cost and trip distance all affect individuals' mode choice between car and motorbike compared with public transport. With regard to the impact of household to individual, individuals with children (age under 18) in households are more likely to choose car than public transport. Individuals with more cars or motorbikes in household tend to use more car or motorbike than public transport respectively.

With respect to the influence of land use variables on mode choice between car and public transport is that higher population density at district-level and higher population density and job density at city/county level associate to higher probability of choosing public transport over the car while more grid-like street pattern intends to attract more car use rather than public transport. In terms of land use influence on mode choice between motorbike and public transport, higher population density at district-level and city/county-level and job density at city/county-level also associate with choosing public transport over the motorbike, more diversified land uses and more grid-like street pattern associate to higher probability of motorbike use. Few studies have paid attention to the effects of land use on motorbike use. This study found that diversified land uses provide more opportunities for access to different activities. Likewise, a grid-like street pattern provides an easy access environment for the motorbike. Chang & Wu[20] characterised motorbike by shorter trip distances and a greater number of multi-stop trips compared to car use. Therefore, diversified land uses and grid-like street pattern are likely to attract more motorbike use and public transport. For Southeast Asian countries with a high proportion of motorbike use such as Taiwan, Vietnam, the Philippines, Malaysia, Thailand and Indonesia, maybe there is a need to implement some strategies to increase the inconvenience or the costs for motorbike use in urban area in order to make public transport more competitive compared to the motorbike. Although there may be an argument that the is preferable to the car in terms of environmental impact, and should therefore be encouraged in order to discourage growth in car use, the motorbike is a step into private motorised transport for people reaching the age of 18 enjoying the right to have driver's license. If people get used to using the motorbike as daily transport mode at the young age, many of them may well shift to car ownership as their income increases and they get older. Therefore, implementing effective strategies to ensure the built environment favours public transport over motorbike use is critical for a sustainable future.

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